This is a postprint version of an article accepted for publication in *Personality and Individual Differences*. Citation should refer to the published version: https://doi.org/10.1016/j.paid.2018.03.024

What Are the Most Powerful Predictors of Charitable Giving to Victims of Typhoon Haiyan: Prosocial Traits, Socio-Demographic Variables, or Eye Cues?

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This project was made possible through the support of a grant from the John Templeton Foundation (Grant ID: 43919) awarded to Paul Van Lange and Thomas Pollet. The opinions expressed in this publication are those of the authors and do not necessarily reflect the views of the John Templeton Foundation. Thomas Pollet is supported by the Netherlands Institute for Advanced Study in the Humanities and Social Sciences.

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Abstract

Major natural disasters often prompt charities to start rallying for extra donations. However, little is known about which variables predict disaster donations most strongly. Here we focused on donations to victims of typhoon Haiyan in the Philippines (2013). A multifaceted approach combined three potential predictors: (a) prosocial traits (social value orientation and social mindfulness, or SVO and SoMi), (b) socio-demographic variables, and (c) minimal social cues (eye images). Participants ($N = 643$) completed an online survey in which they decided whether or not to spend time on a fundraising task to support the typhoon victims. Results of this exploratory study showed that SVO and SoMi, followed by educational attainment and political ideology, were the most prominent predictors of the decision to donate. Furthermore, SVO, SoMi, educational attainment, and religiosity were related to the donated amount. In disaster relief appeals, prosocial personality (and certain socio-demographic factors) might be a more important predictor of helping behavior than exposure to eye images.

Keywords: charitable giving, natural disaster, prosocial personality, education, eye images

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1. Introduction

Major natural disasters tend to prompt a rapid outpouring of solidarity and relief donations (Zagefka & James, 2015). A case in point is typhoon Haiyan that hit the Philippines in 2013 and elicited over $400 million in disaster relief donations within the first month. Despite substantial research on predictors of philanthropy and charitable giving in general (for reviews, see Bekkers & Wiepking, 2011a; Wiepking & Bekkers, 2012; Zagefka & James, 2015), little is known about the predictors of a specific, yet important, type of charitable giving: disaster relief donations.

Disaster donations are unique because they combine features that are usually not evident in donations to regular charities, like the one-off nature of the appeal, the aspect of outgroup help (as the recipients are often outgroup victims in distant lands), and the strong emphasis on the urgency and the dramatic loss incurred by single identifiable victims (Small, 2010; Västfjäll, Slovic, Mayorga, & Peters, 2014). Given those characteristics, disaster donations are often the result of various psychosocial and situational factors that are still not fully understood and are usually examined in isolation (Zagefka & James, 2015). Therefore, the present research aimed to expand the understanding of disaster donations by examining a composite of three juxtaposed factors highlighted by the broader literature (Bekkers & Wiepking, 2011a; 2011b): prosocial values, socio-demographic characteristics, and cues to being watched (i.e., eye images).

1.1. SVO and SoMi

One line of research on charitable giving that could explain disaster donations (specifically) has traditionally focused on social value orientation (SVO), a dispositional factor reflecting the degree and direction of care about others' outcomes in relation to one's own in situations of interdependence (Messick & McClintock, 1968; Van Lange, 2000). SVO predicts various forms of giving, including donations to noble causes, volunteering, and postmortem organ donation (Bekkers, 2006; McClintock & Allison, 1989; Van Lange, Bekkers, Schuyt, & Van Vugt, 2007). Typically, heightened SVO levels are positively associated with helping behavior, due to an increased sense of social responsibility and concern for fairness and equality (De Cremer & Van Lange, 2001; Stouten, De Cremer, & Van Dijk, 2005). Given this evidence, individual differences in SVO should predict donations to disaster victims.

A recently introduced construct that has strong associations with SVO is social mindfulness (SoMi), which can be defined as seeing and considering the needs and wishes of others before making a decision (Van Doesum, Van Lange, & Van Lange, 2013; Van Lange & Van Doesum, 2015). SoMi signals prosocial intentions and is positively associated with self-reported empathy and perspective-taking. Here we examine for the first time the ability of SoMi to predict a specific type of helping, namely donations to disaster victims.

1.2. Socio-Demographic Variables

A second line of research on charitable giving, which could potentially explain disaster donations (specifically), has focused on various socio-demographic variables, including educational attainment, age, political ideology, religion, and gender (Bekkers & Wiepking, 2011b; Wiepking & Bekkers, 2012; Zagefka & James, 2015). Typically, individuals with higher educational attainment and at an older age tend to show greater charitable giving than those with lower educational attainment and at a younger age (Wiepking & Maas, 2009). According to Wiepking and Maas (2009), a likely explanation for the "education-giving" link is that higher educational attainment facilitates understanding of others' needs and, thus, greater willingness to help. Furthermore, higher educational attainment increases access to financial capital, which in turn provides the resources to donate. With regard to age, it has been proposed that older people donate more because of life-cycle and cohort effects (Bekkers & Wiepking, 2011b).

With regard to political ideology, several studies suggest that liberal political attitudes tend to enhance charitable giving (Farwell & Weiner, 2000; Osborne & Weiner, 2015, but see Brooks, 2007). This can be attributed to the link between liberal political attitudes, sympathy for people in need, and adherence to prosocial values (Farwell & Weiner, 2000; Van Lange, Bekkers, Chirumbolo, & Leone, 2012).

The link between gender or religion and charitable giving may be strong but is often contingent on other variables (e.g., the measure of giving or the type of charitable cause or organization). For instance, women appear more likely to give than men, but men give higher amounts on average than women (Wiepking & Bekkers, 2012). Furthermore, being religiously affiliated can increase charitable giving and prosociality (Brooks, 2007). However, such charitable behaviors are often parochial as they can be directed toward members of a religious ingroup (Galen, 2012). Given this evidence, we sought to explore the potential role of each of the aforementioned socio-demographic variables and the interplay between factors in predicting donations to disaster victims.

1.3. Eye Images

A third line of research on charitable giving has drawn attention to cues of social surveillance: For instance, the mere presence of an image of watching eyes is shown to be an effective intervention to enhance charitable giving (e.g., Fathi, Bateson, & Nettle, 2014; but see Northover, Pedersen, Cohen, & Andrews, 2017).

Eye images were specifically selected here because, in contrast to other social cues, they can serve as an easy and cost-effective intervention that has attracted considerable attention from policy-makers and NGO's in recent years.

One explanation for the effect of eye images on charitable giving is that such minimal cues to being watched can trigger a feeling of social scrutiny, which could potentially evoke concerns about one's own reputation (i.e., what others think of me; Oda, Niwa, Honma, & Hiraishi, 2011). Such reputational concerns, in turn, elicit a strong inclination to behave charitably. Besides potential social scrutiny, eyes convey other social information that may enhance disaster donations, such as emotions or gender (e.g., Jessen & Grossmann, 2014). Considering that the emotional content of aid appeals can affect charitable giving (Small & Verrochi, 2009), we sought to examine the effects of eye images and eyes' emotion (but also gender) on disaster donations. More broadly, it needs to be noted that prosocial traits, socio-demographic variables and eye cues have also been associated with donations of time and effort (e.g., volunteering, see Bekkers, 2005, 2010).

In summary, our primary purpose was to carry out an exploratory study of disaster donations. To this end, we focused on responses to a call for urgent help to victims of typhoon Haiyan. We assessed the relative impact of three types of variables on donations in an online setting: (a) prosocial traits (SVO and SoMi), (b) socio-demographic variables (educational attainment, age, gender, political ideology, and religious beliefs), and (c) minimal social cues (eye images). Using a multifaceted approach, we aimed to determine the relative importance of each variable in predicting the decision to donate (yes/no) and the amount of donation.

2. Method

2.1. Participants

The study sample comprised 643 US participants (68.1% women, M_{age} = 29.79, SD_{age} = 9.96), recruited between December 10th and 16th, 2013, from the online platform CrowdFlower. The majority indicated that they were Caucasian (68.9%), followed by Asian, African-American, Hispanic, Mixed, and Native American (10.1%, 7.5%, 6.7%, 2%, and 1.7% respectively). A small minority (3.1%) preferred not to report ethnicity. The university's ethics committee approved the study and participants provided informed consent before participating.

2.2. Procedure

Participants completed the SVO and SoMi measures, and the compulsory part of the typing task (see typing task, below). Next, they read a text about the impact of typhoon Haiyan in the Philippines and answered some comprehension questions. Afterwards, they indicated if they wished to raise financial support for the typhoon victims by volunteering their time to complete extra typing task trials (voluntary part). Money raised through the typing task was donated to the typhoon appeal. While reading the text and deciding whether or not to donate, participants were exposed to a typhoon appeal logo with a picture of eyes or controls (Appendix A). At the end, participants answered certain socio-demographic questions, and received $0.50 for their participation.

2.3. Materials and Measures

2.3.1. SVO. We administered the six primary items of the SVO Slider Measure (Murphy, Ackermann, & Handgraaf, 2011). For each item, participants decided how to allocate a monetary amount between themselves and an anonymous other. To compute participants' SVO index, we calculated mean allocations for self and other for the six items. The inverse tangent of the ratio of those two means produced participants' SVO index (SVO angle). According to Murphy and colleagues (2011), individuals with higher SVO levels (i.e., prosocials) have an angle equal to or greater than 22.45°, whereas individuals with lower SVO levels (i.e., proselfs) have an angle less than 22.45°.

2.3.2. SoMi. Participants completed the SoMi paradigm (Van Doesum et al., 2013). In each of 24 trials, participants were presented with a dyadic situation (i.e., the participant and an anonymous other) in which they were asked to select one of the products displayed on the screen. The ratio of presented products per trial is one unique versus multiple non-unique products (e.g., one blue pen versus multiple black pens). The paradigm consists of 12 experimental trials (one unique versus multiple non-unique products) and 12 control trials (multiple non-unique products), presented in randomized order. The SoMi score was based on participant's tendency to make other-regarding choices in the experimental trials by selecting one of the non-unique products and, thus, leaving a larger variety of product options for the other. Greater proportion of socially mindful choices (1-0) indicated higher levels of SoMi (M = 0.58, SD = 0.25, Mdn = 0.58).

2.3.3. Typing task. This simple, yet time-consuming, task served as the measure of charitable giving (see also Manesi, Van Lange, & Pollet, 2016). The task included two parts: (a) a compulsory part, which served to acquaint participants with the task and included five typing trials (all participants were required to complete this part, but completion did not contribute to charity), and (b) a voluntary part, which was optional (only participants who chose to donate completed typing trials). Inclination to help was measured by choosing to donate by completing task trials of the voluntary part (yes/no decision), and by the amount donated (the number of task trials completed from those who chose to donate). In the voluntary part, every extra task trial (max. 30) that the participant completed helped raise $0.05 for charity (e.g., five extra task trials contributed $0.25, see Appendix B). In this task, participants typed strings of characters with the use of the keyboard. On each task trial, a string of 20 random letters was displayed in the center of the computer screen and participants were asked to type those characters without errors (for an example task trial, see Appendix B).

2.3.4. Eye images. We used 24 different eye images, of which half depicted male eyes and the other half depicted female eyes. Each pair of eyes displayed one of four emotions: joy, anger, sadness, neutral/no emotion. To create the images, we cropped eye regions (279 x 93 mm in size) from 24 standardized facial photographs of three Caucasian adult men and three Caucasian adult women (frontal view). For consistency, the images were taken of the same models from the Radboud Faces Database (RaFD, Langner et al., 2010). The eye image was incorporated into a logo of the disaster relief appeal (Appendix A). For the control group, we used a blank stimulus or a typhoon picture. Each participant was exposed to only one of the eye or control stimuli (26 conditions, in total). The stimuli were transformed to grayscale to eliminate potential color effects on participants' mood and behavior.

2.3.4.1. Pre-rating and selection of eye stimuli. As a first step, 24 RaFD facial photographs were selected based on mean validation data (e.g., percentage of agreement on emotion categorization, mean intensity rating and mean clarity for the facial expression, see Langner et al., 2010). Because mean validation data refer to emotions conveyed through full-face images, at a second step, the eye regions of the selected images were pre-rated for emotion and gender. Specifically, 90 participants from CrowdFlower rated the emotion and gender of each pair of eyes (within-participants design). The order in which the eye images were presented was randomized, and participants were asked to label the emotional expression of the eyes by selecting one of the following options: joy, anger, sadness, neutral/no emotion, other. The order of those choices was randomized across participants and items. Participants also indicated if the eyes belonged to a man or a woman. Final selection of eye stimuli and classification within a single emotion and gender category was based on agreement by at least 80% of the participants (i.e., anger: 92.3%; joy: 81.3%; neutral: 90.1%; sadness: 83.5%, gender: 90.1%).

2.3.5. Socio-demographic questionnaire. The questionnaire included questions regarding political ideology, religious beliefs, educational attainment, gender, age, and ethnicity.

2.3.5.1. Political ideology. We administered two items: "On a scale from left to right (where 0 means *left* and 100 means *right*), what is your political orientation?"; "On a scale from liberal to conservative (where 0 means *liberal* and 100 means *conservative*), how liberal or conservative are you?" The default value of the sliders was 50. On average, participants placed themselves closer to the center on the left-right political spectrum ($M = 47.43$, $SD = 24.48$, $Mdn = 50$) and were self-identified as "moderates" ($M = 48.07$, $SD = 26.03$, $Mdn = 50$).

2.3.5.2. Educational attainment. Participants answered the following question: "What is the highest level of education you have completed?" (eight categories). Of the participants, 8.9% had a postgraduate degree or higher, 25.3% had a four-year university/college degree, 37.9% had a two-year college degree or some college education, and 27.4% had a high school diploma or less (0.5% did not provide information on educational attainment).

2.3.5.3. Religious beliefs. We administered two items. One on religiosity: "On a scale from 0 to 10 (where 0 means *not religious at all* and 10 means *very religious*), how religious are you?"; the default value of the slider was 5. This was followed by a question on religious affiliation: "What is your religious affiliation – Buddhism, Christianity, Hinduism, Judaism, Islam, Agnosticism/Atheism, or other?" Around half of participants had a religious understanding of life to either a moderate or a large extent ($M = 4.37$, $SD = 3.37$, $Mdn = 5$) and identified themselves as Christians (57.2%), followed by Buddhists, Jewish, Muslims and Hindus (3.9%, 3%, 2.2%, and 2%, respectively). The remaining 26.9% of participants reported having no religion or being agnostic, and 4.8% preferred not to answer.

2.4. Statistical Analyses

We chose a bottom-up approach: machine learning, specifically (an extension of) Random Forests. This technique generates many classification/regression trees (Hastie, Tibshirani, & Friedman, 2009; Hothorn, Hornik, Strobl, & Zeileis, 2010; Strobl, Malley, & Tutz, 2009). We used 10,000 trees to discover patterns in data and we focused on algorithms implemented in R (R Development Core Team, 2008), and particularly *ctree* (Hothorn et al., 2010; Strobl et al., 2009). The algorithm can handle correlated data, interactions between variables, and non-linear patterns in the data, and will implement multiple splits along the same variable. It also allows the grouping of categorical predictors, does not overfit, and corrects for multiple testing. This is especially valuable since our study was exploratory and no specific hypotheses were set forth.

These 10,000 trees are generated via the ctree algorithm and are nested in a random forest (here cforest), which can determine *variable importance* (Strobl et al., 2009). Variable importance informs us which variables have little to no predictive ability and which ones do. It is based on the premise that permuting (or shuffling) a predictor variable, which is "genuinely" predictive, should lead to substantially worse predictions (Janitza, Strobl, & Boulesteix, 2013; Strobl et al., 2009).

All analyses were ran in R 3.1.3 (R Development Core Team, 2008) and the *party package*, which is a computational toolbox for recursive partitioning (Hothorn et al., 2010). Extensive information on this data analysis method and the advantages of this approach is provided as electronic supplementary material (ESM 1). Data and R code are available as ESM 2 and 3, respectively (see Appendix C).

3. Results

3.1. Decision to Donate (Yes/No)

The percentage of correctly classified cases was 78.38%. One hundred eighty-eight participants decided to donate. The random forest analysis showed that four variables were largely predictive of the decision to donate: SVO, SoMi, liberal/conservative ideology, and educational attainment (Figure 1). To further understand the underlying pattern, we examined some sample trees. With regard to SVO, the tree algorithm split the variable at an angle of 32.939°, with 347 participants being categorized as proselfs and 296 participants being categorized as prosocials. Note that SVO split at a different angle than the (theoretical) angle proposed by Murphy et al. (2011), which is 22.45°. Results show that prosocials (> 32.939° angle) were significantly more likely to donate to disaster victims as compared to proselfs (≤ 32.939° angle; p = .001, for a sample tree, see Figure 2). Furthermore, participants scoring higher on SoMi (as compared to those scoring lower) were more likely to donate (Table 1). Also, participants who tended to identify themselves as liberal (as compared to those being more conservative) and who had higher (as compared to lower) levels of educational attainment were more likely to donate. Eye images formed the second to least predictive variable (Figure 1). Table 1 presents intercorrelations for the primary variables of interest regarding donating (yes/no decision).

3.2. Amount Donated for Those Who Donate

When analyzing only the data of individuals who donated, cforest revealed that SVO, SoMi, educational attainment, and religiosity were important for predicting the donated amount (Figure 3). SVO, SoMi, and educational attainment had positive associations with the donated amount (based on correlations). Furthermore, correlational analyses showed that religiosity was negatively associated with the donated amount. However, while these variables helped in predicting the amounts of donations in the forest, sample individual trees showed no statistically significant results. No other variables were of substantial and consistent importance in predicting the amount donated. Table 2 presents intercorrelations for the primary variables of interest regarding the amount donated.

4. Discussion

Given the complex nature of disaster donations, the present study is one of the first attempts to pit different powerful predictors against one other. This extends prior research, which has primarily focused on contextual and unilateral explanations (e.g., Zagefka & James, 2015), and helps develop effective appeals for sensitizing the public to donate. Examining donations to victims of typhoon Haiyan, data from 643 participants showed that SVO and SoMi, followed by educational attainment and liberal-conservative ideology, were the most prominent predictors of the decision to donate. Furthermore, correlational analyses showed that SVO, SoMi and educational attainment were positively associated whereas religiosity was negatively associated with the donated amounts (for participants who decided to donate). No interactions were observed in the sample trees.

An interesting finding is that SVO proved to be an important predictor of charitable giving in a large-scale context, involving helping of large communities of unknown others far away. The context is important because SVO is measured in a hypothetical decision-making context involving a dyad. Donating to victims far away is not dyadic, and one could assume that such helping is strongly influenced by feelings of empathy and perceived urgency – features that are not included in the measurement of SVO. As such, the present research provides evidence for the ecological validity of SVO in domains that are large scale, empathic, and characterized by urgency.

Perhaps the most novel finding of the present research is that SoMi was a relatively important predictor of disaster donations – in terms of predictive power. This finding hints at the possibility that SoMi can represent stable individual differences in minding others' control over their situational outcomes. Furthermore, this finding suggests that the SoMi paradigm may have the potential to complement and extend existing game–theoretic methods that predict real-life giving and other-regarding behavior, such as SVO (McClintock & Allison, 1989; Van Lange et al., 2007).

With regard to socio-demographic factors, in line with numerous studies of charitable giving (e.g., Wiepking & Maas, 2009), educational attainment was an important predictor of disaster donations. Extending this past research, the present study shows that higher educational attainment can lead to greater responsiveness to emergency relief appeals. Furthermore, individuals who gravitated toward liberal values (instead of conservative ones) tended to show greater donation likelihood. This result is consistent with past work showing that liberal political attitudes are associated with heightened sympathy and willingness to help people in need (Van Lange et al., 2012).

Interestingly, we found a negative relationship between religiosity and donated amount in our correlational analyses. This may be due to the nature of the charitable cause: Donating to support the victims of typhoon Haiyan is a form of outgroup help. Religious individuals often show heightened charitable behaviors toward ingroup others, but less so toward outgroup others (Galen, 2012). Future studies could explore the relation between religiosity and disaster donations to (religious) ingroups versus (religious) outgroups.

The finding that neither an image of watching eyes nor social information conveyed by those eyes substantially predicted disaster donations adds to the growing debate on the eye-images effect (Northover et al., 2017). Certain methodological reasons may have accounted for the null result. For instance, the exposure time to eye images may have been too long, and this may have resulted in habituation to the stimuli (Sparks & Barclay, 2013). Nevertheless, our results also suggest that eye images are relatively less powerful than prosocial traits in predicting proactive helping in an emergency situation, like a disaster relief appeal.

Certain limitations of this research need to be acknowledged. First, results are likely to apply to international disaster aid only, and cannot be generalized to other types of charities (e.g., domestic aid relief). Second, our measure of charitable giving involves constraints that follow the specifics of the task itself. For instance, certain participants may opt-out of such types of repetitive, cognitive tasks (due to lack of interest). Future studies could focus on different types of disaster relief and include different types of tasks (e.g., tasks requiring physical effort or actual donations) and additional predictors (e.g., socioeconomic status).

5. Conclusions

The contribution of our findings to knowledge is twofold. First, in a crisis situation like a natural disaster, individuals who donate tend to be those who have prosocial personality tendencies, liberal ideology, higher education, and lower religiosity. Second, such emergency situations may be exactly the kind of situations in which minimal cues to being watched may not be crucial, as the urgency of the crisis may draw all the attention. As such, it is important to realize that in these situations, prosocial factors really matter and predict who gives and who does not.

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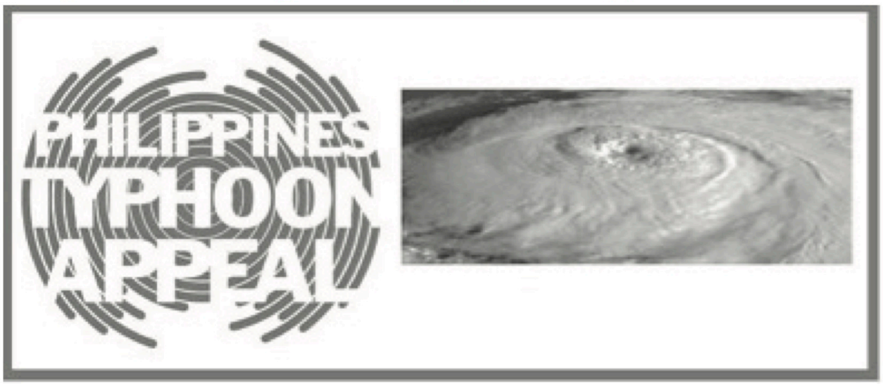
Appendix A

(a) Example eye-logo for the typhoon appeal (with sad female eyes)

(b) Example eye-logo for the typhoon appeal (with happy male eyes)

(c) Example control-logo for the typhoon appeal



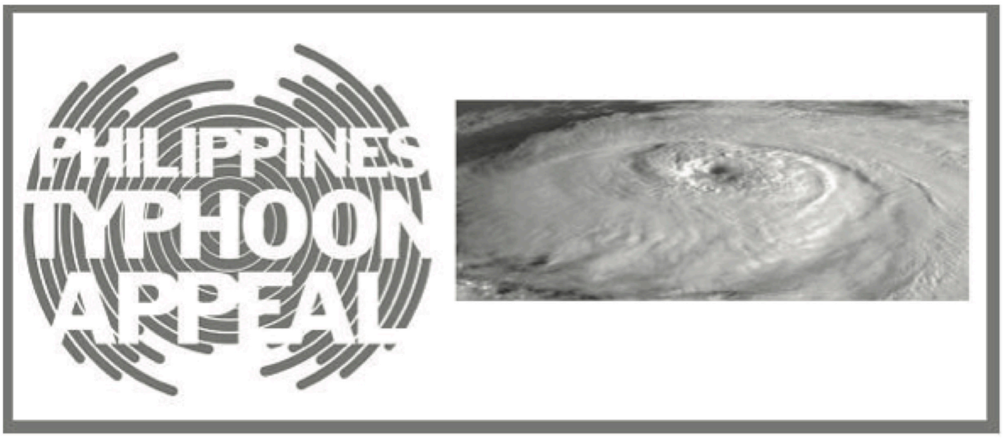
Appendix B

(a) Example typing task trial

Please type the letters that you see below:

knfscgcpmxtojbqyfjov

(b) Example feedback on participant's donation amount
(after completion of five typing task trials)



Your donation = $0.25!

I want to continue donating (with the typing task)

I want to stop donating (with the typing task)

Appendix C

Supplementary data to this article can be found online at:
https://doi.org/10.1016/j.paid.2018.03.024.

Table 1

Correlation Matrix for Study Variables (Decision to Donate)

Variable	1	2	3	4	5	6	7
1. Decision to donate (yes/no)	-						
2. SoMi	.095*	-					
3. SVO	.162***	.190***	-				
4. Religiosity	.009	-.017	.032	-			
5. Political left/right	-.091*	.026	-.094*	.375***	-		
6. Political liberal/conservative	-.081*	.010	-.059	.402***	.566***	-	
7. Age	.065	.047	.026	.177***	.126***	.155***	-

Note. $N = 626$. Decision to donate is dummy-coded (0 = no, 1 = yes). We report Pearson's correlation coefficients.
$*p < .05$, $***p < .001$

Table 2

Correlation Matrix for Study Variables (Amount Donated for Those Who Donate)

Variable	1	2	3	4	5	6	7
1. Amount donated	-						
2. SoMi	.158*	-					
3. SVO	.094	.249***	-				
4. Religiosity	-.025	-.094	.055	-			
5. Political left/right	.048	.084	-.090	.373***	-		
6. Political liberal/conservative	.027	.025	-.112	.506***	.680***	-	
7. Age	.030	-.047	-.069	.309***	.191*	.252***	-

Note. N = 184. We report Pearson's correlation coefficients.
*$p < .05$, ***$p < .001$

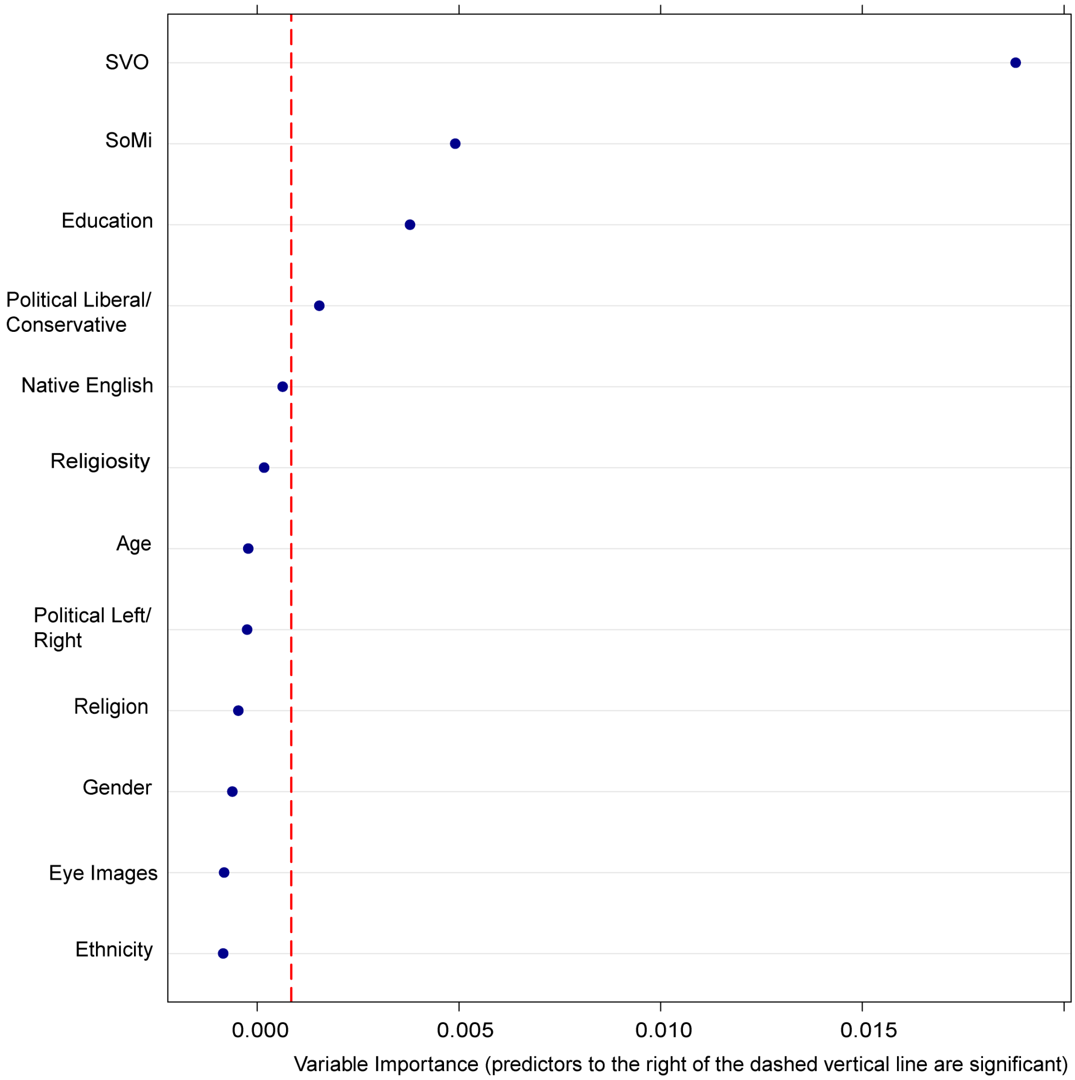


Figure 1. Relative importance of each predictor variable in the decision to donate. The red vertical line serves as a benchmark for variable importance. Variables to the right of the red line are considered better predictors. The percentage of correctly classified cases is 78.38%. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

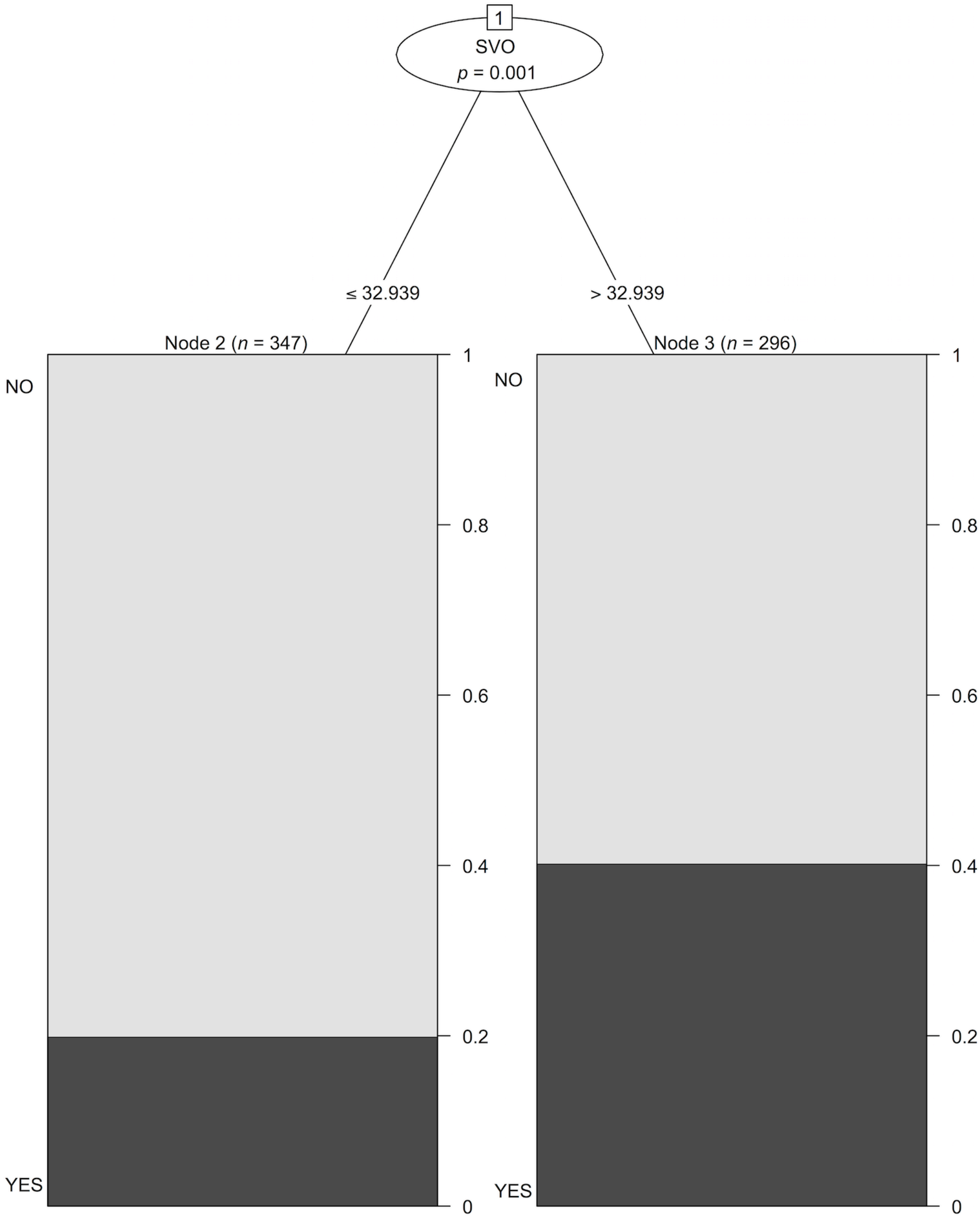


Figure 2. A sample decision tree for the decision to donate (yes/no decision). The algorithm separates based on SVO (p = .001), with prosocials (> 32.939° angle) being significantly more likely to donate than proselfs (≤ 32.939° angle).

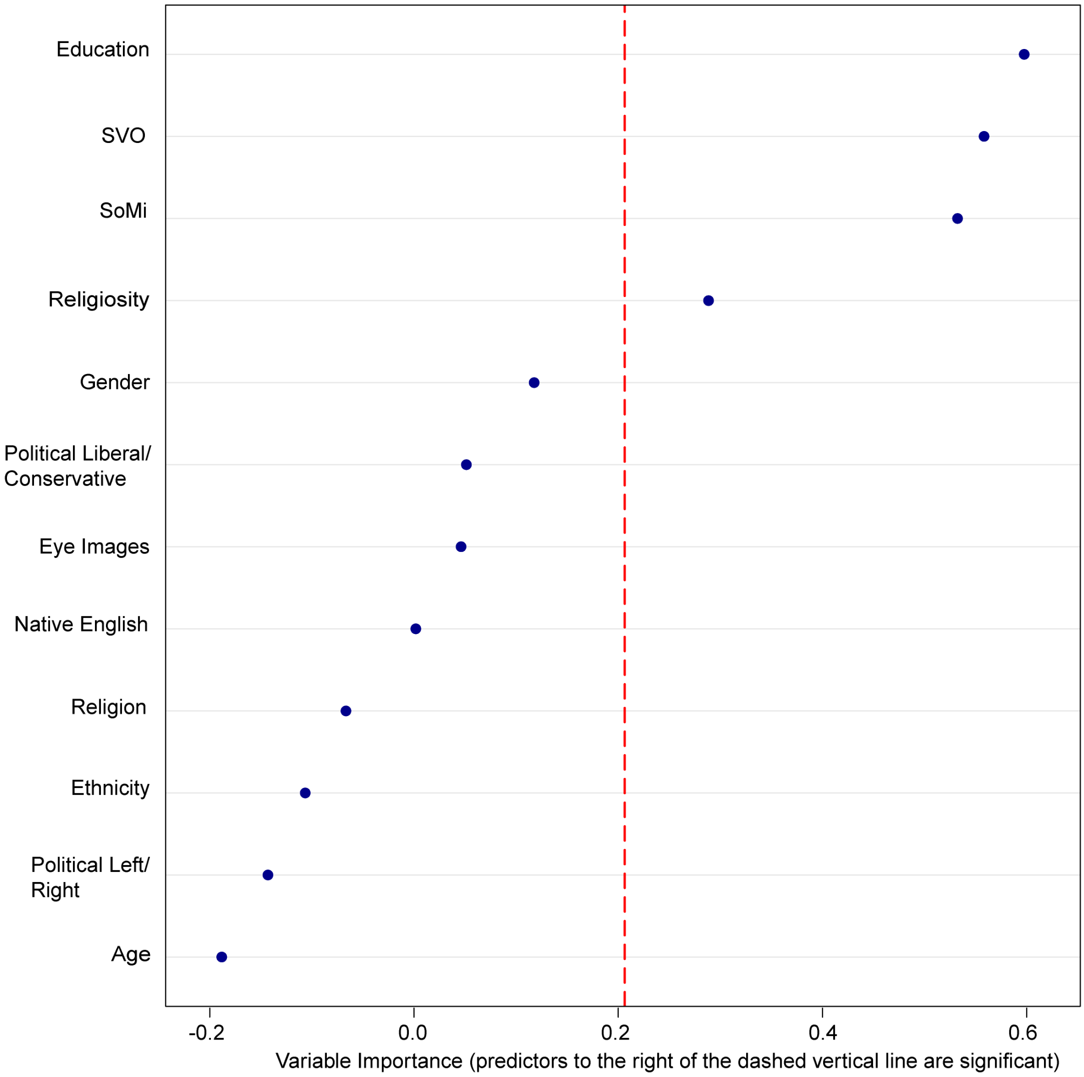


Figure 3. Relative importance of each predictor variable in the amount donated for the participants who donate. The red vertical line serves as a benchmark for variable importance. Variables to the right of the red line are considered better predictors (distinctions are relative rather than absolute). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ESM 1 for "What are the most powerful predictors of charitable giving to victims of typhoon Haiyan: Prosocial traits, socio-demographic variables, or eye cues?"
Manesi, Van Lange, Van Doesum, & Pollet (2018)

Below, we summarize the analytical methods in a non-technical way. Given the limited space, we refer to Hastie, Tibshirani, and Friedman (2009); Hothorn, Hornik, Strobl, and Zeileis (2010); Hothorn, Hornik, and Zeileis (2006); and Strobl, Malley, and Tutz (2009) for a full, technical description (also see our annotated script and Shih, 2011). Our analyses rely on conditional inference trees. Conditional inference trees are part of 'machine learning' algorithms: a set of algorithms commonly used for data mining (Hastie et al., 2009). These algorithms were initially developed to automatically and 'optimally' detect interactions and non-linear patterns in complex data (reviews in Hastie et al., 2009; e.g.: CART: Haughton & Oulabi, 1997). Very simply put, the basic principle is that an algorithm can learn patterns in a training set, which can then be tested on 'unseen' data (out-of-bag) to check if it has 'learned' the correct patterns. By running analyses with many trees and evaluating what is learned, we can derive which variables are predictive and which ones are not. This is done internally in an ensemble learning approach

Here we focus on algorithms implemented in R (Hothorn et al., 2010; R Development Core Team, 2008), and particularly 'ctree': *conditional inference trees* (Hothorn et al., 2010, 2006; Molnar, 2013; Strobl et al., 2009). As described in (Hothorn et al., 2010), the ctree algorithm documents patterns in multivariate data like in a decision tree (Crawley, 2013). This approach allows tracing the relative importance of factors on the outcome of interest (in this case the decision to donate or not), and the dependencies between these factors. The algorithm can handle correlated data, interactions between variables, and non-linear patterns in the data, and will even implement multiple splits along the same variable. It also allows the grouping of categorical predictors. Unlike earlier applications, there is no necessity to 'prune' the decision trees or a risk for overfitting (Hothorn et al., 2010). The statistical inference is done via permutation testing, and accounts for multiple testing (for a full description, see Hothorn et al., 2010, 2006). The algorithm is relatively free of statistical assumptions (in comparison to standard OLS regression or 'standard' decision tree techniques, see Hothorn et al., 2010; Strobl et al., 2009), and has been successfully applied in epidemiology and ecology (e.g., Bureau et al., 2005; Chang et al., 2008; Cutler et al., 2007), but has not been widely used in behavioral sciences yet (but see IJzerman, Pollet, Ebersole, & Kun, 2016; Pollet, 2014; Strobl et al., 2009).

Given the nature of the present research, this approach is preferable over traditional approaches (like a standard regression model). This is because in a traditional approach, we would have to specify all potential interactions, including their non-linear interactions, and we would have to exercise 'error control' by correcting the *p*-values. Via our machine learning approach such multiple testing is accounted for (see the description in Hothorn et al., 2010 on how this is achieved). In cases where we could have a large number of candidate hypotheses such as ours (e.g., one could hypothesize: main effect of SOMI, main effect of SVO, main effect of eyes, main effect of only eyes with certain emotions, interaction between SOMI and certain emotions in the eyes, interaction between SVO and certain emotion of eyes, gender-dependent effect of eyes, gender-dependent effect of eyes dependent on the gender of the participant, religion effect, religion-dependent effect of eyes, etc.), we would have to spell out all these options and weigh these (and correct the *p*-values for multiple testing). Thus, considering that the present study was exploratory, using machine learning allowed for exploring which variables are able to predict the outcome measure in this dataset and which ones are unable. However, a standard logistic regression corroborates the result (i.e., the sample tree for Figure 2, see Supplementary Table 1).

The trees generated via the ctree algorithm often can be nested in a random forest (here a conditional inference forest: cforest – a form of ensemble learning). The premise is that single trees might be unstable, inaccurate, or converge on a local rather than global optimum, as they are based on random training samples of the data. However, on *average* they will be as accurate as can be. A random forest will therefore aim to achieve the best possible, stable prediction, given the set of variables it receives as input. Random forests routinely outperform other common machine learning methods in classification and prediction (Hastie et al., 2009). The random forest allows examining which variables the trees use to cast their vote, which can be used for what is known as 'variable importance' (Strobl, Boulesteix, Kneib, Augustin, & Zeileis, 2008; Strobl et al., 2009). Very simply put: Variable importance tells us which variables have little to no predictive ability, and which ones do. As described by Janitza, Strobl, and Boulesteix (2013:3): *"If the predictor is not associated with the response, the permutation of its values has no influence on the classification, and* *thus also no influence on the error rate. The error rate of the forest is not substantially affected by the permutation and the VI [Variable Importance] of the predictor takes a value close to zero, indicating no association between the predictor and the response. In contrast, if response and predictor are associated, the permutation of the predictor values destroys this association. "Knocking out" this predictor by permuting its values results in a worse classification leading to an increased error rate. The difference in error rates before and after randomly permuting the predictor thus takes a positive value reflecting the high importance of this predictor."* Also see Breiman and Cutler (n.d.) or Strobl, et al. (2008, 2009).

Note that a variable in this framework might be important even if it has no direct effect but only has effects via interactions with other variables (and in opposite directions). Suppose that eye cues have no direct effect on the decision to donate or not, but they increase the likelihood to donate in some subgroup and lower it in another. In such a case, eye cues are an important predictor for donations but have no direct effect.

We presented the results for the conditional inference trees as well as the (standard) variable importance for the conditional random forest. It is important to note that the variable importance is interpreted as a relative ranking rather than an absolute score, in which we followed Shih (2011). The lines we presented in the figures are based on a suggested 'benchmark', the absolute variable importance of the worst predictor in the set of predictors. Simulations suggest that such a benchmark is generally robust (IJzerman et al., 2016).

We evaluated performance via examining the predictions for the actual data, as done in Shih (2011). Following the request by a referee, we also examined the performance in the out-of-bag data and a split into training and test data (75% training, 25% test data). It should be noted that performance on unseen data for the key analyses was at chance level (around 70%, close to the no information rate). Then again, this is not surprising (note that our models do not have tuning, https://stats.stackexchange.com/questions/211748/training-and-test-sets-in-random-forest-regression). In the script, we also provide further metrics and analyses. Note that we are not claiming that this is the best or only way to analyze the data. However, when faced with many predictor variables and exploratory analyses, conditional random forests allow for some useful insights.

All analyses were run in R 3.1.3 (R Development Core Team, 2008) and the party algorithm (Hothorn et al., 2010). We analyzed both the decision to donate as well as the amount donated for those who donate. All analyses were run in duplicate with different starting seeds, the script is included, and we also implemented some robustness checks and additional analyses (for example using the ‘earth’ package).

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Table 1

Coefficients (and Standard Errors) for the Effect of SVO on the Decision to Donate (Yes/No) in a Logistic Regression Model

	Model 1	**Model 2**
SVO		0.030^{***}
		(0.007)
Constant	-0.876^{***}	-1.716^{***}
	(0.088)	(0.236)
N	626	626
Log Likelihood	-379.126	-370.336
AIC	760.252	744.671

Note. AIC = Akaike information criterion.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$